



Epileptic Focus Localization Based on iEEG Plot Images by Using Convolutional Neural Network

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Abstract

Patients with epilepsy need to locate the lesion before surgery. Currently, clinical experts diagnose the lesions through visual judgment. In order to reduce the workload of clinical experts, many automatic diagnostic methods have been proposed. Usually, the automatic diagnostic methods often use only one feature as the basis for diagnosis, which has certain limitations. In this paper, we use multiple feature fusion methods for automatic diagnosis. For the cause of epilepsy: abnormal discharge, we use the filter and entropy to capture the energy features of epilepsy discharge. Due to the epilepsy brain waves contain spike and shape waveforms, short time Fourier transform (STFT) is used to analysis the time-frequency features. In feature fusion, we plot the color map of entropy and spectrogram get from STFT together to combine the different types of features. After the feature extraction and fusion steps, each brain signal is converted into an image. Next, we use the visual analysis capabilities of the convolutional neural network (CNN) to classify the plot image. With the visual recognition ability of CNN, in the experiment, we got a classification accuracy of 88.77%. By using automatic diagnostic methods, the workload of clinical experts is greatly reduced in actual clinical practice.

1 Introduction

Epilepsy is a brain disease caused by abnormal discharges of brain cells. According to the World Health Organization (WHO) statistics, approximately 50 million people worldwide have epilepsy. Epilepsy disease brings a variety of social problems, such as patients need long-term

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medication, some pediatric patients will face the Chilean development, neurological diseases and other problems during their growth. At present, epilepsy patients can control the seizures by taking medications, and some patients can reach a complete cure and stop taking medications. Some patients require long-term medication to control their condition. But there are still some patients with drug resistance. For this part of the patient, the current plan is to remove the lesion by surgery.

Before epilepsy surgery, we need to determine the location of the lesion through physical examination. Intracranial Electroencephalography (iEEG) is the most commonly used examination method. In current clinical practice, iEEG signal is analyzed by a clinical expert's visual diagnosis [1]. Here are some points that need improvement. iEEG recording time is at least two-three days, usually one week. These massive amounts of iEEG data require manual visual diagnosis by clinical experts. Vision diagnosis is an experience dependent process and often requires several years of training. Nevertheless, the diagnostic results given by different experts are not completely consistent, final diagnosis often required by a vote of the diagnostic committee.

In view of the problems and difficulties in the diagnosis process, some automatic diagnosis systems have been proposed. These methods mainly include two steps, feature extraction and classification. In feature extraction, wavelet transform [2, 3, 4, 5] empirical mode decomposition (EMD) [6, 7], entropy [8, 9, 10] time-frequency [11, 12] methods are often used. In classification work, from traditional classifiers support vector machine (SVM) to current neural network based methods EEGNet [13] are often used.

At present, the diagnosis of clinical expert in hospitals is often performed in a variety of ways, visual judgment of brain waves at different scales and frequency domain analysis. However, in the proposed automatic diagnosis methods, a single feature is mainly used, which has limitations on the model. In this paper, we use two different features and fuse the features together to form a new feature image. By this way, two features are combined. Time-series brain signals are converted into pictures, so we can use CNN models for visual recognition. In the feature extraction method, we start from the point that energy is contained in the over discharge, and select a variety of entropy as the features. **When clinical experts make visual judgments, they often make judgments based on whether the brain waves contain spike waves and shape waves.** Brain waves of healthy people are mainly composed of four wave bands: δ : 0.5-4 Hz, adult slow-wave sleep and baby. θ : 4-8 Hz, drowsiness in adults and teens. α : 8-13 Hz, relaxed/reflecting. β : 13-30 Hz, focus, high alert, anxious and so on. The frequency range of spike wave is 14-50 Hz and the frequency range of shape wave is 5-14 Hz. According to the difference in frequency distribution between normal brain wave and spike, shape wave, we use short time Fourier transform to analyze the frequency domain information. During feature fusion, we choose to fuse two different features into an image, so that we can use the powerful visual recognition capabilities of CNN.

The rest of the article is organized as follows: Section 2 describes the feature extraction method include entropy & filter, STFT and plot images. Section 3 describes the CNN model used as a classifier. The results are presented in Section 4, The discussion and summary are described in Section 5.

2 Methods

We start with the pathogenesis of epilepsy and the characteristics of the brain wave, use two different feature extraction methods of entropy and STFT, and fuse the two features into one image. By fusing two features into an image, we convert the brain wave signal into an image, so

we can use the powerful classification capabilities of a convolutional neural network to classify the brain wave.

2.1 Dataset

Bern Barcelona dataset [14] is used to evaluate our method. The dataset is built by the Department of Information and Communication Technologies of the Universitat Pompeu Fabra and the Department of Neurology of the University of Bern. The dataset includes five patients and each patient has long standing pharmaco-resistant temporal lobe epilepsy and is a candidate for epilepsy surgery. The iEEG data is recorded by using the device of AD-TECH (Racine, WI, USA). A total of 15,000 samples, 7,500 focal samples and 7,500 non-focal samples. each sample is 20 seconds with a sampling rate of 512 Hz and filtered by a bandpass filter (0.5-150 Hz, fourth-order Butterworth filter). You can find more information on the website¹. An example of the focal and non-focal iEEG samples are shown in Fig. 1, respectively.

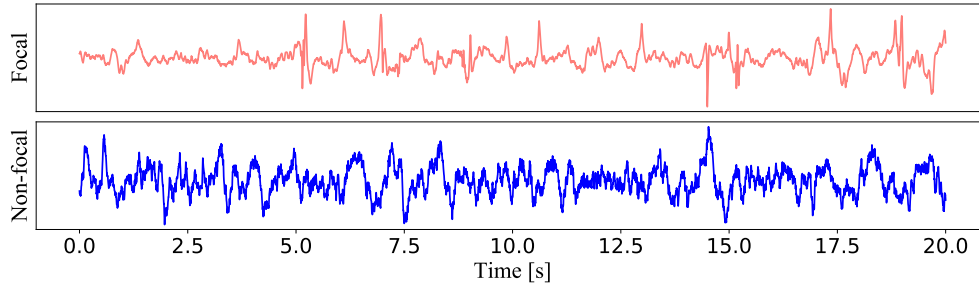


Figure 1: Samples of focal and non-focal iEEG (Bern Barcelona Dataset).

2.2 Entropy & Filter

Consider the cause of epileptic seizures: abnormal discharge of brain cells. The abnormal discharge releases a lot of energy, and we use entropy [15] as a feature extraction method and combined with the filter to extract the features of the iEEG signal. First, we use six bandpass filters (third-order Butterworth) to filter the iEEG data. The bandpass frequencies used are Delta 0.5-4 Hz, Theta 4-8 Hz, Alpha 8-13 Hz, Beta 13-30 Hz, Gamma 30-80 Hz and Ripple 80-150 Hz. After filtering, we calculate eight different entropies for each filtered iEEG data. Eight different entropies are Shannon entropy, Renee entropy, Generalized entropy [16] [17], Phase entropy (two types) [18], Approximate entropy [19], Sample entropy [20] and Permutation entropy [21]. After these two steps, we extract a feature matrix from each sample with a size of 6×8 . The flowchart of feature extraction procedure is shown in Fig. 2.

2.3 Short Time Fourier Transform

When clinical experts diagnose epilepsy, they mainly judge whether the brain waves contain waveforms such as spike and shape waves from the visual point of view. Usually, the frequency of shape is between 5-14 Hz and the spike wave is between 14-50 Hz. Because of the instability

¹<http://ntsa.upf.edu/downloads/andrzejak-rg-schindler-k-rummel-c-2012-nonrandomness-nonlinear-dependence-and>

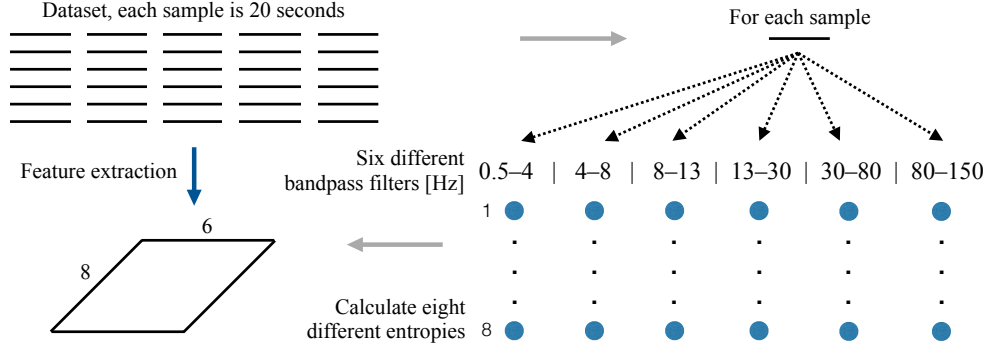


Figure 2: Flowchart of feature extract procedure: Filter & Entropy.

of the iEEG signal, we use the STFT method to replace the Fourier transform [22] for the feature extraction. $x(t)$ is a timing signal, the time-frequency spectrogram can be calculate by (1)

$$STFT\{x(t)\}(\tau, \omega) = \int_{-\infty}^{\infty} x(t)w(t - \tau)e^{-j\omega t} dt \quad (1)$$

where $w(t)$ is the *Hann* window function centered around zero.

2.4 Image Plot

In order to use the visual method to classify the extracted data features. We plot the entropy and spectrogram obtained by the STFT into an image with 224×224 pixels. The example of feature fusion image is shown in Fig. 3, images are randomly selected from the dataset.

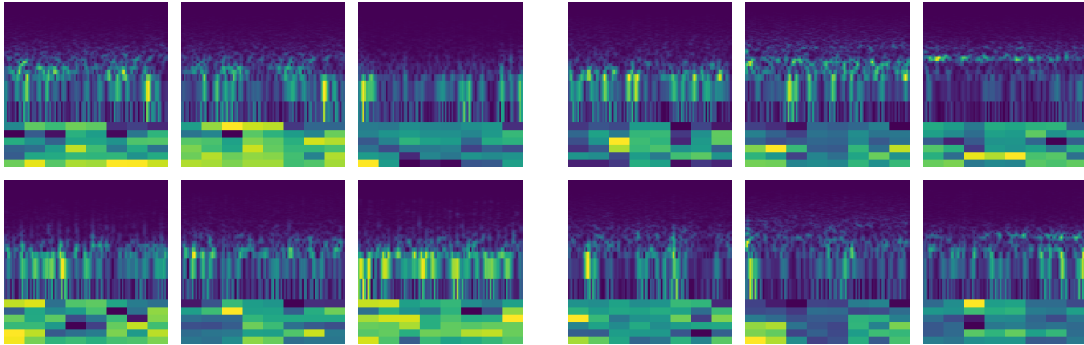


Figure 3: Each image contains two parts, the upper part is the spectrum obtained by STFT, and the lower part is drawn by the feature matrix (color map). The left half is the focal signal, and the other half is non-focal signals.

3 Convolutional Neural Network

The ultimate obtained STFT & Entropy images are fed into CNN model shown as Fig. 4. The proposed CNN architecture has four convolutional layers following three fully connected neural network (FCNN) layers, a max-pooling and a batch normalization layer are set after each convolutional layer to lower the calculation complexity and prevent overfitting. The last layer of the architecture to execute the classification process, in this layer, the input is classified as focal or non-focal.

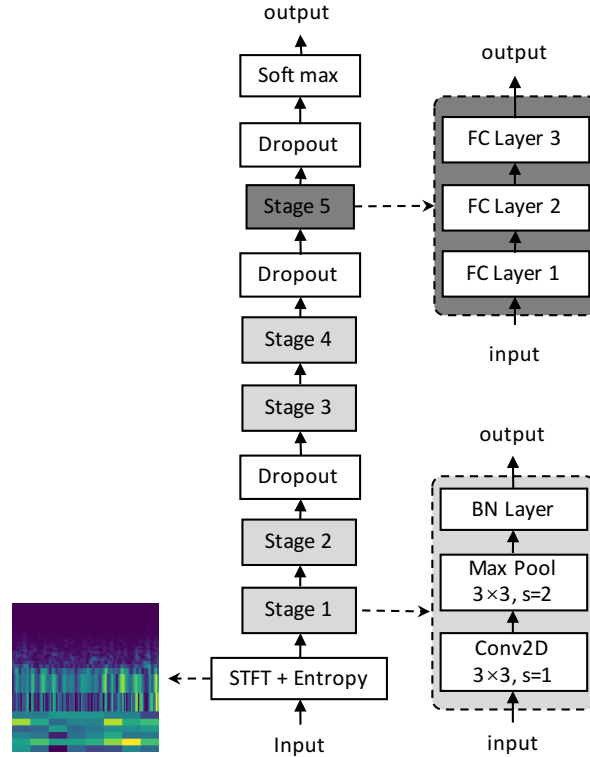


Figure 4: Architecture of CNN model.

4 Experimental Results

In this section, Bern Barcelona dataset is used to evaluate our method. In the dataset, a total of 15,000 samples, focal and non-focal has 7,500 samples, respectively. We use a 10-fold cross-validation method to evaluate the model. Every time, 10% data are selected as a test set, the rest are training sets, at last, every data has been tested once.

As a comparison, we only use entropy feature with a three layers fully connected neural network model, the result is shown in Fig. 5. Another model for comparison is STFT feature with one layer of maxpool and five layers of fully connected neural network, each fully connected layer is followed by a batch normalization layer, the result is shown in Fig. 6. The result of fused features with FCNN model is shown in Fig. 7. The result of fused features with CNN

model is shown in Fig. 8. Comparison of the results of the three models are shown in Table 1.

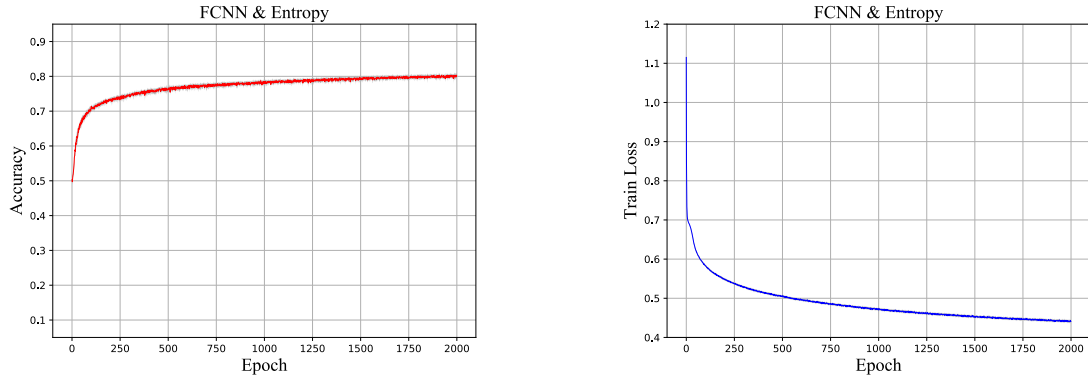


Figure 5: Results of the FCNN model with entropy features. Left: test accuracy vs. number of epochs, red line: Average of classification test accuracy (10-folds), gray area: Standard deviation. Right: Train loss vs. number of epochs, blue line: Average of train loss (10-folds), gray area: Standard deviation.

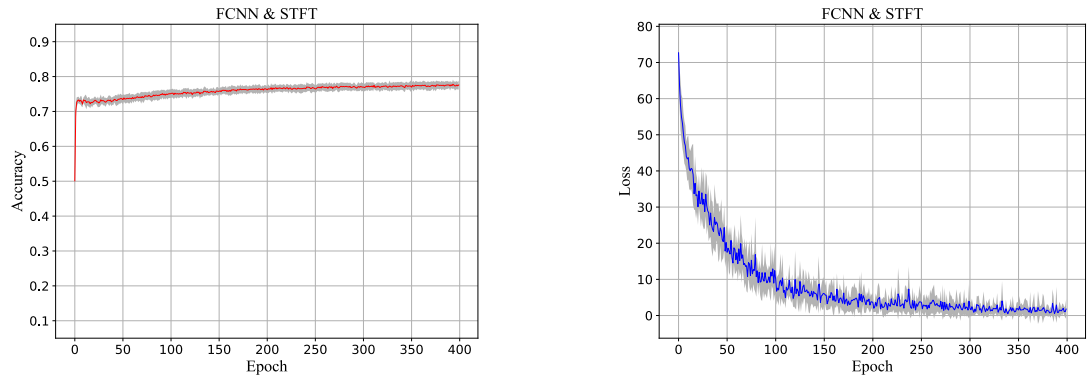


Figure 6: Results of the FCNN model with STFT features. Left: test accuracy vs. number of epochs, red line: Average of classification test accuracy (10-folds), gray area: Standard deviation. Right: Train loss vs. number of epochs, blue line: Average of train loss (10-folds), gray area: Standard deviation.

5 Discussion and Summary

In the article, we proceed from the principle of epilepsy disease, use entropy and short-time Fourier for feature extraction, which corresponds to the abnormal discharge (energy) and spike, shape wave (frequency characteristics) of epilepsy brain signals, respectively. In the traditional method, the extracted feature matrix is usually input into a classifier. In this paper, we plot the extracted feature matrix into an image and then use a convolutional neural network for classification. By this way, we can use the visual analysis capabilities of the CNN model.

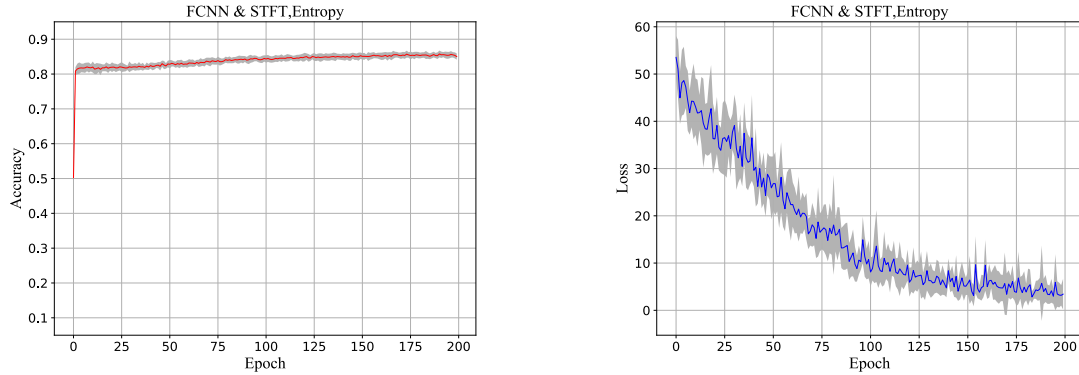


Figure 7: Results of the FCNN model with plot image. Left: test accuracy vs. number of epochs, red line: Average of classification test accuracy (10-folds), gray area: Standard deviation. Right: Train loss vs. number of epochs, blue line: Average of train loss (10-folds), gray area: Standard deviation.

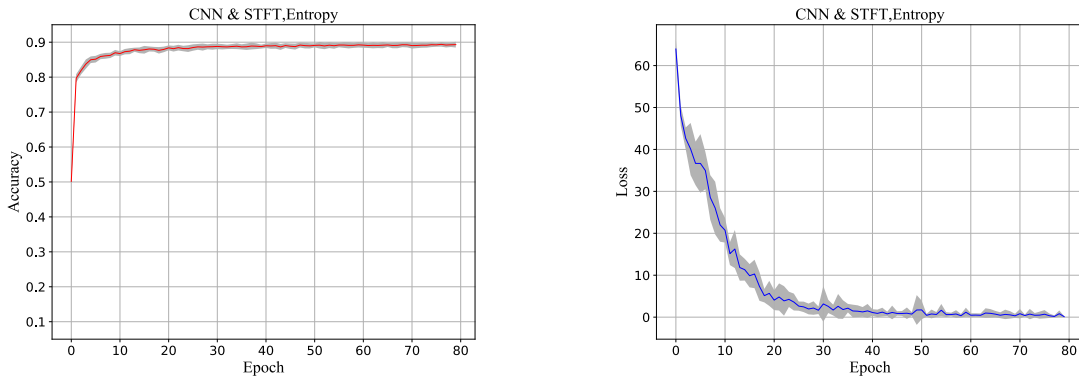


Figure 8: Results of the CNN model with plot image. Left: test accuracy vs. number of epochs, red line: Average of classification test accuracy (10-folds), gray area: Standard deviation. Right: Train loss vs. number of epochs, blue line: Average of train loss (10-folds), gray area: Standard deviation.

Comparison of algorithm performance with other articles are shown in Table 2. The results show that the performance of the model is improved by multi-feature fusion.

Table 1: Results of three models (Mean \pm standard deviation).

Model	FCNN Entropy	FCNN STFT	FCNN Plot Image	CNN Plot Image
Result [%]	80.06 ± 0.16	78.14 ± 0.11	85.47 ± 0.19	88.77 ± 0.16

Table 2: Localization results of focal and non-focal iEEG data of published articles by using the Bern-Barcelona dataset (accuracy in [%]).

Author	Method proposed	Performance
[5]	SVM & DWT	83.07
[3]	LS-SVM & EMD, Entropy	87
[23]	LS-SVM & DWT, Entropy	84
[9]	LS-SVM & TQWT, Entropy	84.67
[6]	SVM & BEMD	86.89
Proposed	CNN & Plot Image	88.77 ± 0.16

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